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## Publication Date
2015-06-01

## DOI
10.1016/j.biocon.2015.03.031

Peer reviewed

Biological Conservation 186 (2015) 287–295

Contents lists available at ScienceDirect

Biological Conservation

journal homepage: www.elsevier.com/locate/biocon

# Using lightweight unmanned aerial vehicles to monitor tropical forest recovery

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ARTICLE INFO

*Article history:*
Received 24 November 2014
Received in revised form 23 March 2015
Accepted 29 March 2015

*Keywords:*
Canopy structure
Costa Rica
Drone
Ecosynth
Hexacopter
LiDAR
Point cloud model

ABSTRACT

Large areas of tropical lands are being removed from agriculture and restored to address conservation goals. However, monitoring the ecological value of these efforts at the individual land-owner scale is rare, owing largely to issues of cost and accessibility. Traditional field-based measures for assessing forest recovery and habitat quality can be labour intensive and costly. Here we assess whether remote sensing measurements from lightweight unmanned aerial vehicles (UAV) are a cost-effective substitute for traditional field measures. An inexpensive UAV-based remote sensing methodology, "Ecosynth", was applied to measure forest canopy structure across field plots in a 7–9-yr tropical forest restoration study in southern Costa Rica. Ecosynth methods combine aerial images from consumer-grade digital cameras with computer vision software to generate 3D 'point cloud' models of vegetation at high spatial resolutions. Ecosynth canopy structure measurements were compared to field-based measures and their ability to predict the abundance of frugivorous birds; key seed dispersers that are sensitive to canopy structure. Ecosynth canopy height measurements were highly correlated with field-based measurements ($R^2 \geqslant 0.85$), a result comparable in precision to LiDAR-based remote sensing measurements. Ecosynth parameters were also strongly correlated with above-ground biomass ($R^2 \geqslant 0.81$) and percent canopy openness ($R^2 = 0.82$). Correlations were weaker with proportion-based measures such as canopy roughness ($R^2 = 0.53$). Several Ecosynth metrics (e.g., canopy openness and height) predicted frugivore presence and abundance at levels of accuracy similar to those of field-based measurements. Ecosynth UAV remote-sensing provides an effective alternate methodology to traditional field-based measures of evaluating forest structure and complexity across landscapes. Furthermore, given the volume of data that can be generated in a single flight plan, as well as the ability to use the technology in remote areas, these methods could expand the scope of studies on forest dynamics and recovery when combined with field-based calibration plots.



## 1. Introduction

Secondary tropical forest cover is increasing rapidly in some regions, particularly in hilly, montane landscapes that are marginal for agriculture (Asner, 2009), due to both natural regeneration and active restoration (Aide et al., 2013; Lamb, 2011). This trend is driven by a complex set of drivers and is facilitated by increasing interest in the role that forest recovery may play in sequestering carbon as part of efforts to reduce emissions from deforestation and forest degradation (REDD+, Edwards et al., 2010; Harvey et al., 2010). An ongoing challenge to such efforts, however, is cost-effective monitoring, particularly for landowners at the local level (De Sy et al., 2012).

Assessments of forest recovery in degraded landscapes typically focus on a number of parameters such as the abundance of tree recruits, community composition of vegetation, structural dynamics such as plant height and branching architecture, or measures of habitat quality in terms of their use by different animal guilds (e.g., Rodrigues et al., 2013). Structural complexity, and in particular plant height, is often strongly associated with increased visitation by avian frugivores, which can lead to greater tree seed dispersal and seedling recruitment (Duncan and Chapman, 1999;

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http://dx.doi.org/10.1016/j.biocon.2015.03.031
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McDonnell, 1986). Estimates of tree height, in conjunction with diameter at breast height and wood specific gravity, can also be used to estimate aboveground carbon accumulation or stock (Chave et al., 2005). Accordingly, these measures can evaluate how a particular site is responding to a restoration intervention (Holl and Zahawi, 2014), determine if management practices have impacted forests (Imai et al., 2009), or assess how biomass changes in response to a particular pressure such as climate change (Phillips et al., 2011). Collecting these data in the field, however, is time consuming, expensive, and requires skilled field technicians. Additionally, site access can be complicated if it involves multiple landowners. Long-term monitoring of forest recovery and restoration projects is critical to evaluating success and providing guidance on how to invest scarce resources, but such monitoring is commonly inconsistent or lacking (Melo et al., 2013; Ruiz-Jaen and Aide, 2005), in part due to cost.

Alternate approaches to evaluate change in forest structure and composition using remote sensing technology have shown promise in alleviating the need for time consuming and costly field-methods, and may provide additional parameters for assessing habitats that are not logistically feasible with on-the-ground field surveys (Mascaro et al., 2014). Of the remote sensing technologies available, Light Detection and Ranging (LiDAR), which uses laser pulses to determine distances between structures, as well as spectral imaging (hyperspectral, multispectral), have all shown potential value for ecological applications. LiDAR data can quantify structure in three-dimensions (3D), and this information can be used to evaluate habitat suitability for different fauna (Goetz et al., 2007; Jung et al., 2012; Turner, 2014; Vierling et al., 2008), estimate tree height with a high degree of accuracy (Andersen et al., 2006), and determine aboveground biomass and carbon density (Asner et al., 2012; Goetz and Dubayah, 2011; Lefsky et al., 2002) among other applications. Although application of LiDAR to ecological problems has shown great promise, conventional airborne LiDAR acquisitions remain prohibitively expensive for most monitoring projects and field-studies as a typical acquisition costs at least $20,000 per flight, regardless of the size of the study area (Erdody and Moskal, 2010).

Recent advances in remote sensing using lightweight unmanned aerial vehicles (UAV; Fig. 1) (Anderson and Gaston, 2013) are providing an alternate option using digital images and computer software. With costs running from as low as $300 to a few thousand dollars (Koh and Wich, 2012; Schiffman, 2014), UAVs can potentially provide researchers and technicians with a field-portable remote sensing device that enables low-cost collection of data when and where needed. The 'Ecosynth' methodology (http://ecosynth.org/) processes large sets of overlapping digital photographs using open-source software and computer vision 'structure from motion' algorithms to create 3D models of aboveground vegetation (Dandois and Ellis, 2010, 2013). The information is made available in the form of 3D 'point clouds', wherein each individual data point has 3 coordinates describing the horizontal and vertical position of a surface viewed within the photographs, together with red–green–blue (RGB) colour information. Such

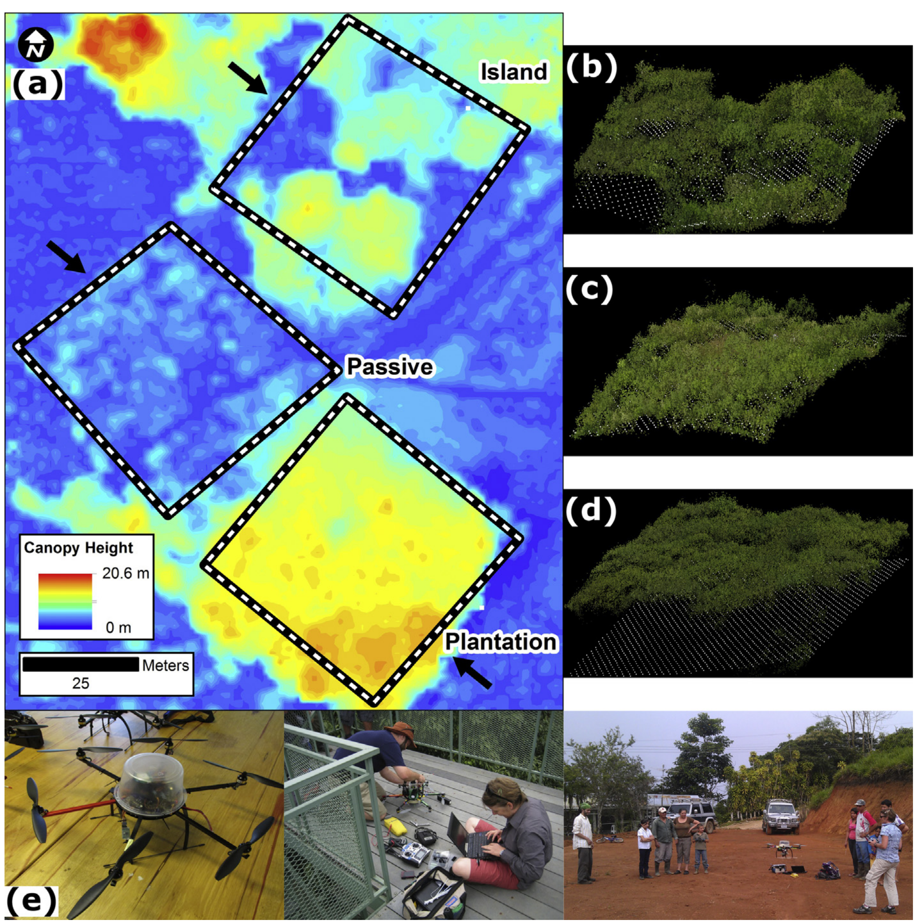


**Fig. 1.** Overhead view of an Ecosynth *non_GPS* canopy height model (CHM) (a) of one field site showing the three restoration treatments, each outlined by hatch marks. Right panels show oblique views of the Ecosynth 3D-RGB point cloud for the island (b), passive (c), and plantation (d) treatments as in (a) with the *non_GPS* DTM represented as a 1 m grid of white points; approximate viewpoint indicated by black arrow. Photos (e) from left to right: hexacopter; prepping a hexacopter for a flight; and an automated landing approach at a field site.

point cloud data can then be used to estimate a number of ecologically important variables similar to those LiDAR technologies can provide, including canopy height models, canopy structure and roughness metrics (Dandois and Ellis, 2010, 2013), and can potentially be used to estimate above-ground biomass or carbon accumulation. Although Ecosynth technology has produced high precision results for canopy height and structure in relatively homogenous, forested terrain, the ability of these methods to accurately assess vegetation structure and habitat quality in more remote study sites with rough, undulating terrain and variable vegetation cover has not been evaluated.

A vital component of estimating canopy height and structural metrics from any 3D remote sensing product is the ability to accurately characterize ground topography in the form of a Digital Terrain Model (DTM; Drake et al., 2002; Evans and Hudak, 2007). For LiDAR data, this is carried out by classifying 'ground' and 'non-ground' points using terrain-filtering algorithms. However, prior research has shown that such algorithms do not work well when applied to Ecosynth point clouds in areas of dense canopy cover due to the paucity of understory points registered, such that the best results are obtained when a high resolution LiDAR DTM is available (Dandois and Ellis, 2010, 2013). No existing LiDAR DTM was available for the region, a situation that persists across most of the world (Goetz and Dubayah, 2011). Accordingly, two alternate methods were used to generate DTMs: (1) terrain filtering algorithms were applied to Ecosynth point clouds; and (2) sub-meter precision differential GPS elevations collected in the field were interpolated.

In this study, we use Ecosynth methods to derive measures of canopy height, structural complexity, and canopy openness for 13 ~1 ha restoration sites in a long-term study in a mountainous area of southern Costa Rica. Ecosynth metrics from both models were compared to field-derived structural data to evaluate their accuracy. We also evaluated the capability of Ecosynth and field-based structural measures to predict frugivorous bird presence using data collected in restoration sites. We chose frugivores as they are key seed-dispersers into restoration sites and lack of seed rain is a primary limiting factor in tropical forest regeneration (e.g., Wijdeven and Kuzee, 2000).

## 2. Material and methods

### 2.1. Study Site

This study was carried out at 13 ~1-ha restoration sites established across $a \sim 100\ \mathrm{km}^2$ area between the Las Cruces Biological Station (8°47′7″N; 82°57′32″W) and the town of Agua Buena (8°44′42″N; 82°56′53″W) in southern Costa Rica. Sites are in the tropical premontane wet forest zone (Holdridge et al., 1971), range in elevation from 1060 to 1430 m a.s.l., and receive a mean annual rainfall of 3.5–4 m with a pronounced dry season from December to March. Mean annual temperature is ~21 °C. All sites are separated by a minimum of 700 m, and the surrounding landscape is a highly fragmented mosaic of mixed-use agricultural fields, pasture, and remnant forest patches. Sites are on highly uneven terrain and most are steeply sloped (15–35°). All were farmed for ⩾18 years for crop cultivation, coffee farming, and/or cattle grazing before restoration treatments were applied (Holl et al., 2011).

At each site we established three 0.25-ha (50 × 50 m) restoration plots, each separated by a minimum of 5 m. Plots received one of three randomized restoration treatments, which included a "passive" strategy (cattle excluded, no seedlings planted), an active "plantation" strategy (mixed-species trees planted throughout plot), and an intermediate "island" strategy (same mixed-species trees planted but in patches with unplanted spaces between). We planted seedlings of four tree species, *Erythrina poeppigiana* (Walp.) Skeels and *Inga edulis* Mart. [both Fabaceae], *Terminalia amazonia* (J.F. Gmel.) Exell [Combretaceae], and *Vochysia guatemalensis* Donn. Sm. [Vochysiaceae]. Planting density was kept constant (~2.8 m distance between trees). Plantations were uniformly planted, whereas the island treatment was planted with six islands of tree seedlings of three sizes: two each of 4 × 4, 8 × 8 and 12 × 12 m [see Holl et al. (2011) for site setup details]. Sites were established between 2004 and 2006; nonetheless, mean tree height and cover development overlapped substantially among planting years because of high variability in tree growth rates (Holl and Zahawi, 2014; Holl et al., 2011).

### 2.2. Data collection and analysis

#### 2.2.1. Field measurements

*2.2.1.1. Canopy height.* Canopy height was measured with a Leica Disto laser range finder (±1 cm) between June and August 2012. In passive and plantation treatments, canopy height was assessed at the corners of each of four 8 × 8 m permanent sampling quadrats ($n = 16$ points/treatment/site); one quadrat was randomly placed within each of the four 25 × 25 m treatment quadrants (excluding the outer 5 m buffer of the plot). Due to the patchy planting methodology in islands, canopy height was assessed at six points in each of the six islands; measurement locations included island interior (2), perimeter (2), and exterior (2) ($n = 36$ points/island treatment/site). If no tree canopy was present, the height of pasture grasses and shrubs was determined with a tape measure. Average field height was calculated for each treatment plot, hereafter *field height*.

*2.2.1.2. Above-ground biomass.* Above-ground biomass (AGB) was determined for all treatment plots in a separate study in 2012 (Holl and Zahawi, 2014) using field-based measures of diameter at breast height of planted and naturally-establishing trees ⩾1 cm diameter at breast height, wood specific gravity for individual species, and an above-ground biomass model for moist tropical forest (following Chave et al., 2005). As height is considered a good predictor of biomass (Drake et al., 2002; Lefsky et al., 2002), field estimated AGB was compared to Ecosynth generated height estimates to assess how accurately remotely sensed data can predict biomass (Dandois and Ellis, 2010, 2013).

*2.2.1.3. Canopy structure – openness and roughness.* Percent canopy openness within each treatment was estimated by taking densiometer readings at 1 m height within the permanent sampling quadrats in June and July 2013 ($n = 16$ for plantation and passive treatments; $n = 30$ islands). The standard deviation of field height was used as a proxy for canopy roughness where higher values indicate a more uneven canopy height.

*2.2.1.4. Frugivorous birds.* Frugivorous birds were surveyed at 12 sites on six separate occasions by a single observer in July and November 2011; April, July and November 2012, and in April 2013 (Reid et al., 2014). Frugivores included species that consume fruit as a significant portion of their diet (Appendix 1); seed predators (*e.g.*, Psittacids) were excluded. To account for functional differences within the frugivore guild (Wheelwright, 1985), we divided frugivores into small (<100 g) and large (>100 g) categories. Restoration plots were actively searched for 20 min in random order, and all birds seen or heard within the plot were recorded. Surveys were conducted between sunrise (~5:30) and 9:00 AM. Birds flying over plots were not censused.

#### 2.2.2. Remote sensing measurements

*2.2.2.1. Image data collection.* Images were acquired using a commercially available, hobbyist 'multirotor hexacopter' UAV using the methods of Dandois and Ellis (2013) and based on the Arducopter flight computer (3D Robotics Inc.; http://copter.ardupilot.com/). The hexacopter (diameter 0.6 m; payload ~1.5 kg; Fig. 1e) was configured for aerial imaging with a Canon ELPH 520 HS 'point-and-shoot' digital camera pointed at nadir and calibrated to an 18% grey card in full sun (Dandois and Ellis, 2013). The UAV was equipped with a lithium-polymer electric battery allowing for a maximum flight time of ~15 min. The total cost for all UAV components was USD $1500.

For each flight, the UAV took-off, ascended to a predetermined flight altitude, flew a parallel track course by GPS control, and then returned and landed at the launch site automatically. One site (3 treatment plots) was covered for each preprogramed flight path, which included a 50 m buffer minimum with the following specifications: altitude 30–40 m above the upper canopy surface; speed 6 m $s^{-1}$; photographic overlap > 90% forward, 75% side to side; camera frames 2 $s^{-1}$; camera resolution 10 megapixels. All flights were flown in July 2013.

*2.2.2.2. 3D Point cloud generation.* A Trimble GeoXT 2008 differential GPS unit was used to record the elevation and launch location of each flight by collecting one position per second for the duration of UAV setup and flight (~22 min/site ≅ 1300 positions), considered a nominal length of time for improving GPS location accuracy (Andersen et al., 2009). Launch locations were differentially corrected using Trimble Pathfinder software to a nearby publicly available base station. Coordinates were exported to the WGS84 UTM Zone 17 N projected coordinate system with average precision of 0.35 m horizontal and 0.54 m vertical.

3D multi-spectral RGB point clouds (mean density 55 points $m^{-2}$) were generated from the digital images collected at each site using Agisoft-Photoscan computer vision Structure from Motion software (http://www.agisoft.ru; v0.9.1 64-bit build 1703). Such software produces 3D reconstructions by applying computer vision and photogrammetric algorithms to simultaneously solve for the location of images with respect to each other, and to the objects viewed within them (see Dandois and Ellis (2013) for further details). Point clouds were geo-referenced to the WGS84 UTM Zone 17N projected coordinate system and post-processed to noise-filtered point cloud products following Dandois and Ellis (2013). Prior to running Agisoft-Photoscan, image sets were trimmed to remove those recorded during take-off and landing by manually identifying changes in UAV direction at the start and end of a flight within the images (see Appendix 2 for further details).

*2.2.2.3. Digital terrain and canopy height models.* Two methods were used for generating DTMs: (1) terrain filtering algorithms were applied to Ecosynth point clouds directly (*non_GPS* method); and (2) an understory terrain surface was interpolated based on sub-meter precision differential GPS elevations collected in the field at each treatment (*GPS* method). *Non_GPS* DTMs were produced for each site by terrain filtering with MCC-LiDAR software v2.1 (http://sourceforge.net/p/mcclidar/wiki/Home/; Evans and Hudak, 2007), which applies a threshold filter to the point cloud at different scales to estimate whether a point is a local low point (ground) or not (non-ground; see Appendix 2 for further details). *GPS* DTMs were produced from GPS elevation points obtained using a Trimble GeoXT differential GPS unit with sub-meter precision at each 50 × 50 m treatment plot corner and an additional 2–4 high and low spots relative to an imagined plane, if the treatment terrain could not be considered smooth. *Non_GPS* and *GPS* points were interpolated separately into a 1 m gridded raster DTM by natural neighbour interpolation in ArcGIS 10.1 (ESRI, Redlands, CA). Separate canopy height models (CHM) were then derived for each restoration treatment within each site using the two aforementioned DTMs (hereafter *non_GPS_CHM* and *GPS_CHM*, respectively) by subtracting the underlying DTM value from the elevation of each point in the point cloud, which can be represented visually in a number of ways (Fig. 1a–d; see Appendix 2 for further details).

*2.2.3. Data analysis*

*2.2.3.1. Canopy height and AGB.* Summary statistics of canopy height were extracted from each CHM for all points with height > 0 m on a per treatment plot basis ($n$ = 39 plots). Multiple height metrics were extracted for each CHM including mean, minimum, maximum, median, SD and CV, as well as a number of quartile heights (Dandois and Ellis, 2010, 2013). Other proportion-based metrics such as crown isle, defined as the proportion of a given treatment where the canopy has a height greater than 2/3 of the 99th percentile of all heights within the treatment (Jung et al., 2012), were also determined. The optimal height metric for each CHM was selected after comparison to field height using simple linear regression and was based on the highest correlation coefficient ($R^2$) and lowest root mean square error (RMSE). The same height metrics were regressed against field estimated above-ground biomass. One-way ANOVA followed by Tukey's HSD ($P < 0.05$) was used to compare differences in Ecosynth generated height measures among restoration treatments.

For both sets of CHMs, two outliers were identified based on a Grubb's test (Grubbs, 1969). For one outlier, height overestimation was in part due to the fact that Ecosynth estimates of canopy height quantify all points that fall within a treatment boundary (when observed from above), which can include points from tree crowns that have stems rooted outside the treatment and therefore were not included in field surveys (Appendix 3). To remove these points, the location of crown stems in relation to the treatment boundary was determined by manually delineating tree crowns and then estimating stem location as below the centroid of each crown (Appendix 3). Ecosynth cloud points associated with crowns for which stems fell on or outside the treatment boundary were excluded from overall estimates of canopy height to resolve the outlier problem. The second outlier was problematic due to a dense surrounding closed canopy which likely impaired DTM filtering and reduced the accuracy of GPS-based DTM measurements (Evans and Hudak, 2007). This plot was removed from all further analyses ($n$ = 38 plots total).

*2.2.3.2. Canopy structure – roughness and openness.* A 1 × 1 m gridded CHM raster surface was generated for each treatment plot based on the median point cloud height value within each grid cell. Canopy structure measurements for openness and roughness were then computed following Jung et al. (2012) using Python (v2.7.2; https://www.python.org/, accessed 2014-09-20) and the ArcGIS 10.1 ArcPy geo-processing module (ESRI, Redlands, CA). Ecosynth canopy openness was computed as the proportion of the treatment area that was < 2 m in height. Ecosynth canopy roughness was computed as the average of the absolute deviation of each pixel from the average CHM height across each treatment. One-way ANOVA followed by Tukey's HSD ($P < 0.05$) was used to compare differences in canopy openness and roughness measures among restoration treatments.

*2.2.3.3. Frugivorous birds.* Frugivore detections were analysed using generalized linear mixed effects regression with the lme4 package (version 1.0-6) in R (v 3.0.2) (Bates et al., 2014; R Development Core Team, 2013). For small frugivores, we used the total number of detections over the six survey periods as the response variable. Large frugivores were detected less frequently, so a binary detection/no detection response variable was used. Field and Ecosynth predictors were standardized by dividing by the mean in order to compare effect sizes. We included site as a random factor to account for spatial autocorrelation in bird communities. Small frugivore detections approximated a normal distribution (Shapiro–Wilk W = 0.978, $P > 0.05$), so we modelled them using a Gaussian distribution with identity link. Large frugivore detections were analysed using binary error and logit link. $P$-values for individual predictors of small frugivore detections were produced using the ANOVA function in the car package (Fox and Weisberg, 2011). We used AIC scores corrected for small sample sizes to compare models (Burnham and Anderson, 1998). Goodness-of-fit was evaluated by comparing deviance from full models with deviance from a null model that included the intercept and random site effect.

## 3. Results

### 3.1. Canopy height and AGB

The median Ecosynth height metric was the best overall predictor of field height for both canopy height models (*GPS_CHM* $R^2 = 0.87$, *non_GPS_CHM* $R^2 = 0.85$) and was therefore used for all subsequent comparisons. Mean Ecosynth height values were similar but slightly weaker ($R^2 = 0.83$ & 0.85). Overall, both CHMs were in close agreement and were correlated strongly with field height (Fig. 2a and b) and field-determined above-ground biomass (Fig. 2c and d).

Treatment level height comparisons were similar for the *GPS_CHM* ($F_{2,35} = 14.66$, $P < 0.0001$) and *non_GPS_CHM* ($F_{2,35} = 59.84$, $P < 0.0001$), with plantation ⩾ islands > passive, depending upon the model used ($P < 0.05$). The *GPS_CHM*, however, was a much better predictor of field height and AGB in plantation treatments (Table 1), despite consistently under-estimating field height (Fig. 2a). Both models were poor predictors of field height and AGB in the passive recovery treatment, the *non_GPS_CHM* especially so, whereas they produced similar results for island treatment correlations. The *GPS_CHM* was used for all subsequent calculations and analyses, as it produced stronger correlations at the treatment level (Table 1).

### 3.2. Canopy structure – openness and roughness (GPS_CHM only)

Ecosynth canopy openness varied significantly among treatments ($F_{2,35} = 12.83$, $P < 0.0001$) and was highest in the passive recovery treatment whereas plantations and islands were similar ($P < 0.05$). Ecosynth canopy openness accurately predicted field-measured percent canopy cover (Fig. 3). Ecosynth canopy roughness differed among treatments ($F_{2,35} = 8.67$, $P < 0.001$) and was significantly greater in islands than in the plantation and passive treatments, which were similar ($P < 0.05$). However, canopy roughness correlated somewhat poorly with the standard deviation of field height (Fig. 4), which is used as an indicator of canopy roughness in field-based measures. Correlations at treatment level were no better ($R^2 = 0.20–0.51$).

### 3.3. Frugivorous birds (GPS_CHM only)

Ecosynth and field measurements made similar predictions of avian frugivore detections. For large frugivores, the most-supported model included Ecosynth canopy openness (% dev. = 0.28, $P = 0.004$; Appendix 1). Models using Ecosynth- or field-height had nearly as much support ($\Delta AIC_c = 1.9$, 2.9), and vastly outperformed a model using categorical restoration treatments ($\Delta AIC_c = 49.5$). For small frugivores, the most-supported model used field height (% dev. = 0.12, $P < 0.001$), however, similar predictions were found for a model using the Ecosynth canopy height model ($\Delta AIC_c = 3.7$; Fig. 5).

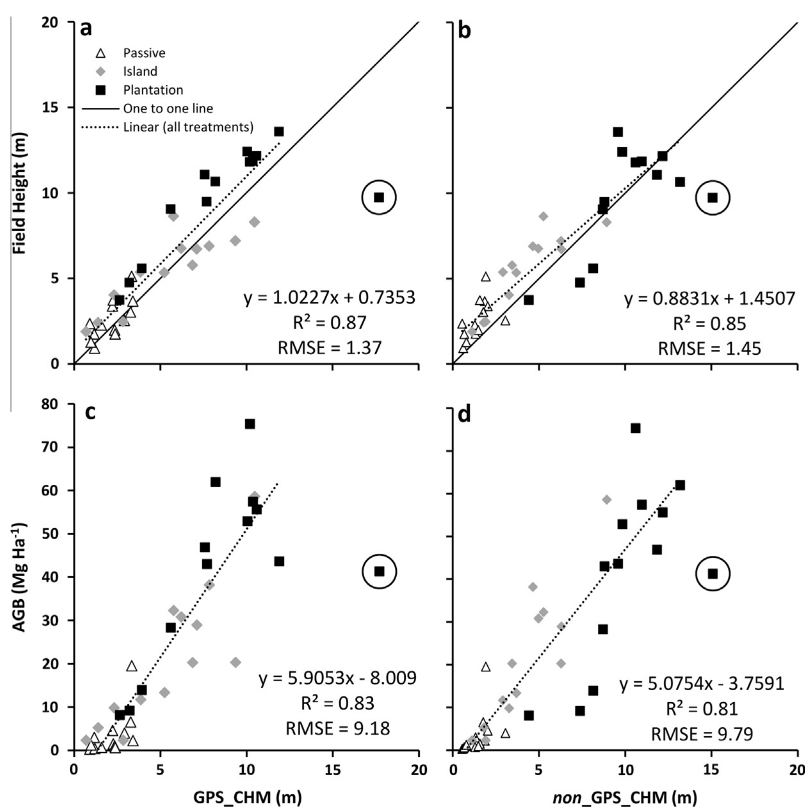


**Fig. 2.** Median Ecosynth cloud point canopy height models (*GPS_CHM* and *non_GPS_CHM*) as predictors of field height (a) and (b), and above-ground biomass (AGB) (c) and (d). Regression is for all treatments ($n = 38$ points). Circled point is an outlier (Grubbs, 1969) and was not included in analysis.

**Table 1**
A comparison of GPS and *non_GPS* canopy height models. Correlation coefficients ($R^2$) and root mean square error values (RMSE; in parentheses) of both canopy height models are presented for field height (FH) and above-ground biomass (AGB) for all treatments combined and per treatment.

| Canopy height model | *GPS_CHM* | | *non_GPS_CHM* | |
|---|---|---|---|---|
| | FH $R^2$ and RMSE (m) | AGB $R^2$ and RMSE (Mg $Ha^{-1}$) | FH $R^2$ and RMSE (m) | AGB $R^2$ and RMSE (Mg $Ha^{-1}$) |
| All treatments ($n = 38$) | $0.87^{***}$ (1.37) | $0.83^{***}$ (9.18) | $0.85^{***}$ (1.45) | $0.81^{***}$ (9.79) |
| Passive ($n = 13$) | $0.51^{*}$ (0.85) | $0.31^{*}$ (4.49) | $0.32^{*}$ (1.00) | 0.18 (4.88) |
| Island ($n = 13$) | $0.77^{***}$ (1.13) | $0.72^{**}$ (9.08) | $0.77^{***}$ (1.11) | $0.81^{***}$ (7.41) |
| Plantation ($n = 12$) | $0.94^{***}$ (0.81) | $0.75^{**}$ (11.47) | $0.61^{*}$ (2.14) | $0.68^{**}$ (12.92) |

* $P < 0.05$.
** $P < 0.001$.
*** $P < 0.0001$.

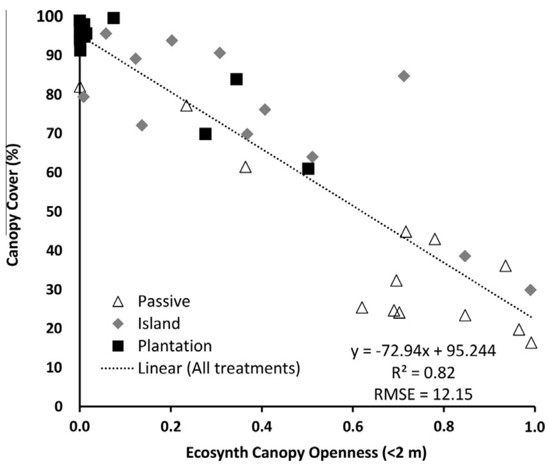


**Fig. 3.** Ecosynth canopy openness (areas with vegetation < 2 m) derived from the *GPS_CHM* as a predictor of percent canopy cover determined in the field with densiometer readings taken at ~1 m ($n = 38$ points, outlier not shown).

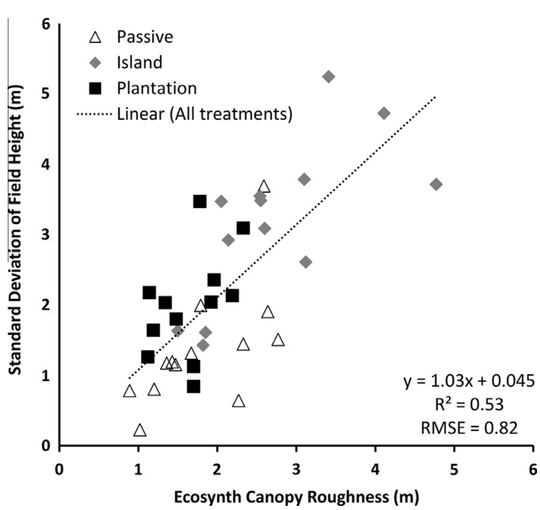


**Fig. 4.** Ecosynth canopy roughness derived from the GPS canopy height model (*GPS_CHM*) and plotted against the standard deviation of field height ($n = 38$ points, outlier not shown).

## 4. Discussion

### 4.1. Canopy height and AGB

Ecosynth canopy height models (CHMs) were strong predictors of field height regardless of whether a DTM was created directly from the Ecosynth point cloud using a filtering algorithm

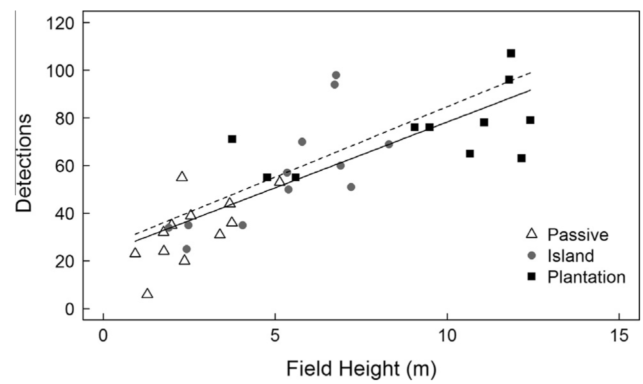


**Fig. 5.** A comparison of Ecosynth- and field-height models for predicting small frugivore detections. The solid line shows the prediction of a model using field height (% dev. = 0.21, $p = 0.018$); the dashed line shows the prediction of a model using the Ecosynth *GPS_CHM* (% dev. = 0.24, $p = 0.017$). Appendix 1 shows a full model comparison.

(*non_GPS_CHM*) or from differential GPS measurements of the terrain (*GPS_CHM*). Similarly robust correlations were found with field based estimates of above-ground biomass. Treatment-level height comparisons from Ecosynth agreed well with field measurements made earlier (Holl et al., 2013), and at levels comparable to prior studies carried out in temperate deciduous forest plots when a high resolution LiDAR DTM was available for determining CHMs (Dandois and Ellis, 2013). Accuracy was also similar to what is generally achieved using LiDAR remote sensing (Andersen et al., 2006; Lefsky et al., 2002). Taken together, results indicate that Ecosynth remote sensing can accurately estimate forest structural metrics across sample sites in patchy landscapes of mixed vegetation cover even where high resolution, high accuracy LiDAR-generated DTMs are unavailable. This is especially important given the current scarcity of LiDAR coverage; the most popular online LiDAR database covers an area equivalent to only ~2% of the continental US (OpenTopography, 2014).

Although the overall accuracy of both Ecosynth CHMs was strong, errors were substantial when vegetation heights were low (passive treatment). Weak correlations were likely due to the lack of height variation among passive treatment plots, most of which ranged between 1.5 and 4.0 m. DTM error was also proportionally greater in low stature measures (Appendix 2), impacting the accuracy of results. Accordingly, remote sensing of this kind is less likely to be useful for assessing subtle differences in height of low stature plants (for example in grasslands); further refinement of the technique is needed for improving measurement accuracy in such systems. Nonetheless, strong differences were found across the range of plots and treatments, which is the strength of this application.

The two models were considerably more reliable in estimating taller vegetation. Plantation canopy heights were predicted more accurately by the *GPS_CHM*, although values were consistently underestimated. In turn, the *non_GPS_CHM* showed a weaker correlation for plantations. Areas of steep slope, dense vegetation, and continuous canopy cover can be challenging to estimate using terrain-filtering algorithms (Evans and Hudak, 2007; Appendix 2). Accuracy could be improved by laying out bright or reflective targets in gaps and outside of densely forested treatments, in order to assist filtering algorithms and provide targets for GPS measurements that can serve as 'ground control' for aligning point models in 3D space (Wolf et al., 2014). In turn, a more advanced GPS system with a nearby reference base station would further improve point cloud georeferencing and terrain elevation estimates. Nonetheless, producing a DTM from point clouds by filtering algorithms (*non_GPS_CHM)* is tedious and time-consuming; GPS-based DTMs (*GPS_CHM*) are preferable if the option exists, especially given that these have slightly higher predictive ability and need only be produced once.

Both models showed strong correlations with field based above-ground biomass estimations, suggesting that the methodology could be used to estimate carbon accumulation in recovering habitats. This is an important result given the need for cost-effective ways for land-owners to estimate carbon storage and verify the efficacy of REDD + programs (Asner et al., 2012; De Sy et al., 2012). As with field-based measures, wood density would need to be determined for target species to improve the accuracy of calculations (Chave et al., 2005). A major strength of this application, however, is the relative ease with which the rate of biomass accumulation can be assessed once data have been calibrated with field-based measures.

### *4.2. Canopy structure and frugivorous birds*

Comparisons of cross-treatment differences in Ecosynth canopy openness were similar to those quantified using field-based densiometer measurements (Holl et al., 2013), and a strong correlation between Ecosynth and field-measured data was found. Ecosynth canopy roughness comparisons showed that island treatments have more heterogeneous canopy cover than passive or plantation treatments, which is consistent with results of field-based measures (Holl et al., 2013). Despite similar treatment level results, Ecosynth data correlated relatively poorly with the standard deviation of height, which is often used as a field-based proxy indicator of canopy roughness.

Ecosynth vegetation structure metrics significantly predicted avian frugivore detections, and results were similar to predictions using field-based metrics. Ecosynth-based variables, including canopy height and openness, explained three times more deviance in large frugivore detections than categorical restoration treatments used in previous studies (Reid et al., 2012, 2014). This is an especially important result as large frugivores, such as toucans, are particularly important for seed dispersal as they are capable of carrying large, late-successional tree seeds. These results complement prior research, which showed that both LiDAR- and Landsat-based measures of canopy complexity were strong predictors of bird species richness (Goetz et al., 2007; St-Louis et al., 2014) and bat activity (Jung et al., 2012). In general, frugivore detections increased as canopy height and structural complexity increased, which coincides with prior studies including one that used the framework of this study (Lindell et al., 2012; McDonnell, 1986), but detections decreased as the amount of large gaps, open space, and short vegetation increased. This result was expected given that increased structural complexity provides greater opportunities for niche partitioning as well as greater overall habitat volume (MacArthur and MacArthur, 1961).

### *4.3. Application of ecosynth computer vision remote sensing to monitor forest recovery*

Ecosynth is a portable remote sensing technology suitable for individual use as a field tool for measuring and mapping canopy height, carbon accumulation, and canopy complexity as a proxy measure of frugivorous bird abundance across recovering tropical habitats. Given the volume of data that can be captured across landscapes, Ecosynth methods have the potential to reduce field time and thereby expand the scope of projects otherwise restricted by the logistics of more traditional field-based surveys. Once the overall workflow has been established, data on canopy structure at the scale of 10's of hectares can be turned around in as little as a day. An added strength is the ability to capture data in remote areas where field-surveys are hampered by logistical constraints and time-consuming methods, e.g., on very steep slopes. Nevertheless, measurements made using Ecosynth and other remote sensing methods must still be calibrated against field-based measures to ensure accuracy and results are still constrained by the quality of DTMs available for estimating heights (Dandois and Ellis, 2013).

Ecosynth UAV missions are carried out at relatively smaller spatial scales (i.e., tens of hectares) as compared to LiDAR missions, which tend to cover 10's to 1000's of square kilometres. This is a key strength of Ecosynth methods, making them ideal for plot-level assessments in the field, while enabling the capture of highly specific canopy structural and spectral traits at high spatial resolutions and high temporal frequencies (e.g., weekly, monthly). For example, Ecosynth has been used to observe the dynamics of forest canopy structure and spectral phenology at the scale of individual tree crowns in temperate deciduous forest plots (Dandois and Ellis, 2013). Similar observations can be made in tropical habitats where repeated Ecosynth measures of canopy structural traits, combined with species abundance observations, could provide valuable insights on species phenology that would be challenging to collect by field methods alone.

Ecosynth point clouds can be used to compute canopy structure metrics that are difficult to estimate using traditional field-based measures. For example crown isles, sharp changes in the height of canopy crowns, or the presence or density of canopy and subcanopy layers at different heights of interest (e.g., 5–10 m; >15 m; <10 m) were all extracted from Ecosynth data with relative ease (Appendix 1). Some of these metrics, such as a <5 m canopy openness cutoff, were found to be important for predicting frugivore abundance. The field of view also differs – with traditional ground-based measures that 'look' up and remote sensing techniques, such as Ecosynth, that look down. Here, Ecosynth metrics may more accurately reflect how treatments are perceived by target groups of interest that also look down, such as frugivorous birds. For example, in one field plot of this study, trees rooted outside the plot (and hence excluded in field surveys) had canopies that covered areas inside the plot boundary. Ecosynth quantified this discrepancy in terms of canopy structure and height metrics that differed significantly from field-based measures, creating an apparent 'outlier' but one that might more accurately reflect the perceived view of frugivorous birds (Appendix 3).

Additional metrics not evaluated in this study, such as combined 3D structural and spectral information, may highlight aspects of canopy habitat that are important to species abundance and diversity of fauna (e.g., Davies and Asner, 2014) but are difficult to observe without frequent and possibly intrusive field observations. Deriving measures of the timing and abundance of fruits and flowers, the age of leaves, tree structural architecture, or the presence of snags, are all important ecosystem function indicators (e.g., Murcia, 1997; Reich et al., 2004; Thies and Kalko, 2004) and have the potential to be derived from Ecosynth 3D-RGB point clouds (Dandois and Ellis, 2013).

Still, as with all techniques, there are challenges. Foremost is that Ecosynth UAV methods require a degree of technical skill that is not mastered quickly. Though most flight sequences can be pre-programmed, it is still necessary to learn basic flying skills, particularly in awkward take-off and landing environments, and if the need to manually takeover a flight arises. Second, substantial background knowledge, most efficiently gained by professional training, is needed in order to program a flight, process images, and georeference and process point cloud datasets. This includes the ability to use GIS and other fairly sophisticated remote sensing software. Third, some mechanical understanding of UAVs is useful, especially for work in remote areas where technical support may be absent. Fourth, and perhaps most importantly, the accuracy of canopy height data is strongly dependent on accurate terrain data, which are not always available. Although two different methods for acquiring terrain data were available, and both worked well here, this may not be the case in sites completely covered by dense vegetation and in areas where GPS base stations are not available to assist with differential correction of GPS measurements made in the field. Finally, although UAVs may ultimately prove less expensive than field surveys, the methodology can rapidly become expensive should accidents occur inflight (or otherwise). Strong familiarity with UAV work in the field is essential to avoid this, ideally coupled with redundant equipment on site.

Ecosynth UAV-based remote sensing can be used to accurately characterize habitat and biomass metrics at small spatial scales, providing field scientists with a LiDAR-like remote sensing tool that can be deployed on demand in the field. The methodology is highly promising and provides ecologists with a powerful tool to assess and monitor forest dynamics in many regions. While not a replacement for field-based surveys, the mobile nature of the technology and its relative ease of application mean that its use can greatly expand the reach and breadth of most field-based projects.

## Acknowledgements

We would like to thank J.M. Chaves-Fallas and J.A. Rosales for assistance in the field with hexacopter flights. Field support for this project was provided by NSF grant DEB 09-18112; the Ecosynth team at UMBC (http://ecosynth.org) was supported by NSF grant DBI 11-47089.

## Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.biocon.2015.03.031.

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